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The medium-term effect of R&D on firm growth

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Abstract This study analyses the effect of R&D expenditure on firm employment growth in the medium term, using six cross-sectional waves of an innovation survey conducted in the Netherlands in all sectors. The analysis is focused on firms having positive R&D expenditure and investigates whether higher investments in R&D (in proportion to firm turnover) translate into higher medium-term growth rates. Comparisons with growth on a shorter term are conducted by following the firm size evolution since the R&D investment for five consecutive years and allowing for firm exit. At all time terms, quantile regression techniques indicate that a higher R&D has a positive effect on high growers and allows a higher number of firms to be high growers. Still, once a firm invests in R&D, even if a higher investment makes the firm more likely to have a very good performance, it does not make it less likely to have a bad one.

Keywords Firm growth · R&D expenditure · Industrial dynamics · Quantile regression

JEL Classifications L20 · L10 · O32 · L26

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1 Introduction

This paper examines the relation between R&D expenditure and firm employment growth from the short to the medium term. The recent literature has confirmed that firm level analysis is necessary to capture the heterogeneity of the economy (Reichstein et al. 2010). A current challenge for economic researchers is then expanding the Gibrat's Law approach (Gibrat 1931) to understand how such heterogeneity can be explained (Stam 2010). In particular, the processes generating high-growth firms have become the focus of attention of several works (Henrekson and Johansson 2010). Supported by a strong and diverse theoretical framework (Nelson and Winter 1982; Aghion and Howitt 1992; Dosi et al. 1995; Pakes and Ericson 1998; Klette and Griliches 2000), innovation is one of the usual suspects in defining differences in performance (and especially sustained performance) among firms. Indeed, stimulating R&D is an important way to increase the growth rate of the "elite-growth" firms (Stam and Wennberg 2009). Connecting more explicitly R&D and innovation patterns with what is known about firm growth is thus a challenge for current research (Cefis and Orsenigo 2001).

Heterogeneity in growth patterns can exist for the same levels of R&D, due to the uncertain nature of the R&D process, both in terms of its length, and its outcome. Yet, even among successful investors, heterogeneity persists: while innovators are likely to enjoy superior employment growth with respect to non-innovators, the bulk of this differential derives from the exceptional job creation activities of a few firms (Freel 2000). Indeed, innovation facilitates the high growth of "superstars", as well as the establishment and continued existence of profitable companies that do not seek to become large enterprises (Tether 1997); understanding the diversity that exists within the population of innovative firms is thus essential to elaborate appropriate innovation policies. The diversity of growth within a population of innovative firms can be represented by means of a distribution of growth rates, conditional to innovation success. Quantile regressions may allow the researcher to avoid the innovator/non-innovator dichotomy and analyse the variations of the distribution of growth rates, conditionally to different levels of innovation (Coad and Rao 2008; Hölzl 2009; Segarra and Teruel 2014). Our study instead employs quantile regressions to investigate how different levels of R&D expenditure affect the (conditional) distribution of firm growth rates, where also the heterogeneity in the length and the outcome from the R&D investment are explicitly taken into account.

Due to the trade-off between the labour-saving and labour-creating effects of innovation (Smolny 1998; Harrison et al. 2014; Hall et al. 2008), the net impact of R&D expenditure on *employment* growth is ambiguous. If we implicitly assume an ideal pattern linking, unidirectionally, R&D to innovation to productivity to employment growth (where direct intermediate steps linking nonadjacent rings of this chain are also possible), our study will take into account only the first and the last rings of this chain, such information integrating the probability that the innovation process would fail. Indeed, entrepreneurs need to be informed about the distribution of returns to R&D, given their own characteristics. If insufficient, they would follow less risky growth strategies such as imitation (Nelson and Winter 1982). Consequently, our independent variable of interest will be only R&D expenditure and growth in terms of firm employment will be the dependent variable. As Coad (2009) states, "employment growth can be seen as an input (in the production process) but also as an output if, for example, the policy maker is interested in the generation of new jobs"(Coad 2009, p. 70).

Existing works linking R&D expenditure to firm growth fail to find appreciable influences of R&D on growth, "in contrast to aggregate evidence which clearly shows that R&D and innovation lead to higher growth at the country level" (Hölzl 2009). One possible explanation of this paradox is that firm-level growth is often measured only one or 2 years after the R&D expenditure (e.g. Klomp and Van Leeuwen 2001; Coad and Rao 2008), while a "long time lag [is] required for a commercially valuable discovery to finally materialize in terms of growth of sales or profits" and "successful R&D may even entail further short-term costs (e.g. costs related to product development) before yielding long-term benefits" (Coad and Rao 2010).

Our paper thus expands the existing empirical evidence on the complex relation between R&D expenditure and firm employment growth in three directions. First, acknowledging that the innovation process is largely uncertain, we expect to observe winners and losers among investors. We thus depart from a conditional mean analysis and investigate how the *shape* of the firm growth rate distribution changes when conditioning the distribution on different levels of R&D expenditure. Second, because of the duration of the innovation process itself, we expect that the impact of R&D on firm growth takes some time to emerge. We thus consider different time lags in order to get a clearer picture of the *evolution* of firm growth in the years following the firm's R&D investment. However, many technical problems arise when considering medium-term performance, as shown in Sect. 4 (on methodology). Notably, only a few studies on growth performance have considered a medium or long term, the main exceptions being analyses by Brouwer et al. (1993) and Stam and Wennberg (2009) (the latter following a cohort of start-ups over 6 years), and some recent works on the effect of firm strategies on growth (e.g. Pelham and Wilson 1996; Leitner and

Güldenberg 2010). Our third contribution therefore consists in adapting our measurement and estimation tools so that firm exit can be identified and dealt with.

Our findings show that R&D expenditure exerts a positive influence on firm employment. However, this influence is largely asymmetric as it appears only when considering high quantiles of the conditional growth rate distribution. Moreover, we observe that the effects in the short and medium terms generally converge.

The structure of the paper is as follows. In Sect. 2, we describe the theoretical background and previous empirical evidence our strategy builds upon. Section 3 presents the dataset and the variables, in particular our original measure of firm employment growth. Next, the econometric methodology is discussed in Sect. 4, and the results in Sect. 5. Finally, Sect. 6 concludes.

2 Theoretical roots and previous empirical evidence

The mechanisms linking R&D, innovation success and firm performance at the firm level are largely indebted to the Schumpeterian endogenous growth representation, according to which firms strive to innovate so that they can enjoy monopoly rents (Aghion and Howitt 1992; Klette and Griliches 2000). The forward-looking firm makes a decision over its level of research input, based on expected returns to R&D (in terms of sales or directly in terms of profits) that affects the stochastic innovation process. Innovation success in turn automatically raises the firms' profitability or productivity level (Aghion and Howitt 1992; Pakes and Ericson 1998; Klette and Griliches 2000). Such stochastic and optimizing representation has however been challenged by models in which boundedly rational agents search for more productive techniques in an uncertain environment, in which the impact of innovation on firm growth is itself random (Nelson and Winter 1982). In such a framework, firms are heterogeneous in their ability to innovate, not only because of their financial resources, but also because they differ in terms of their ability to reach for technological opportunities. R&D must be then viewed as a source of new information feeding the innovation discovery, but also as a way to develop the firm's ability to exploit external knowledge (Cohen and Levinthal 1989). Such path dependency, or innovation cumulativeness, explains the concentration of innovations in the hands of a limited number of firms (Dosi et al. 1995), and ultimately, the presence of persistently outperforming firms (Capasso et al. 2014). The heterogeneous outcomes of innovation efforts motivate an analysis of the whole growth rate distribution, conditional on the firms' level of R&D expenditure.

More interested in the organizational issues related to the innovation process, the management literature has modelled it as a series of operations and strategic decisions. Besides describing the evolution from a linear, sequential innovation model to a more flexible, holistic one (Takeuchi and Nonaka 1986; Rothwell 1994), these studies take into account product development time (Adler et al. 1995; Galanakis 2006). Griffin (1997b, 2002) and Barczak et al. (2009) provide actual measurements of product development time across industries, firms and types of project in the USA. In particular, both industry and firm characteristics account equally for the observed heterogeneity in average product development time (Griffin 1997a). They also show that trying to increase the innovation speed to be the first on the market and reap the monopolistic rents is not always a cost-efficient strategy. Moreover, it contains the firm within small-step innovation processes (Rothwell 1994), given that "[n]ewer, bigger, more complex, more technically challenging and more innovative projects are all associated with longer development times or increases in time" (Griffin 2002, p. 292). As a consequence, we may expect the impact of R&D expenditure on firm growth to differ at different time lags. For instance, the impact of the more radical innovations on firm growth would be visible only in the medium term.

If R&D and subsequent innovations are anticipated to improve sales growth, productivity and profitability,[1] the result is more ambiguous when it comes to employment growth. Put it simply, labour-saving process innovations may create what has been referred to as "technological unemployment" (the labour-destruction effect), while the demand-creation product innovations would support the firm's expansion,

[1] The theoretical assumptions presented above have been confirmed to hold across countries in the empirical tests by Crepon et al. (1998), Parisi et al. (2006) and Hall et al. (2009) on productivity, Jefferson et al. (2006) on profitability, and the studies reviewed in Coad and Rao (2008) on sales growth.

notably in terms of employment (the labour-creation effect). This trade-off was first put forward by David Ricardo in his chapter "On Machinery"[2] and was later modelled by Smolny (1998). It has motivated a thorough analysis of the differentiated impact of product versus process innovations on employment by Harrison et al. (2014) (on data from France, Germany, Spain and the UK) and Hall et al. (2008) (on Italian data). Using slightly different methodologies, both studies disagree on the existence of a displacement effect of process innovations, but converge on a positive impact from the commercialization of new products. If these considerations inform us about the mechanisms at place, they only focus on the second step of the innovation process, taking technical success as given. Other studies concerned with the latter have put forward the role of human resources management (Rammer et al. 2009) and labour skills (Leiponen 2005) as complements to R&D to ensure innovation success. These findings provide empirical support to Cohen and Levinthal (1989) and Dosi et al. (1995): by enhancing learning, R&D expenses develop competitive advantages (Zahra and George 2002) and have a cumulative effect on firm performance. Differently from both streams of research, we estimate the relation between R&D expenditure and firm growth without considering the intermediate logical steps in terms of innovation success and productivity changes. By doing so, we are technically close to Hall (1987), Greenhalgh et al. (2001), Brouwer et al. (1993) and the recent works by Stam and Wennberg (2009), Hölzl (2009), Hölzl and Friesenbichler (2010) and Segarra and Teruel (2014). Both considering large manufacturing firms, Hall (1987) (for the US) and Greenhalgh et al. (2001) (for the UK) find a positive impact of R&D investments on 1-year employment growth. In a sample of 859 Dutch manufacturing firms, Brouwer et al. (1993) show a negative impact of the growth of R&D intensity on the 5-year compound employment growth rate, though the share of product-related R&D displays a positive effect. The authors control for selection bias by the means of a Heckman model; however, the correction term in the second stage regression is insignificant.

More recent contributions are centred on young and high-growth firms (HGFs). Using the Community Innovation Survey for 16 EU countries, Hölzl and Friesenbichler (2010) find that HGFs present a higher R&D intensity than other firms only in countries close to the technology frontier. Following a cohort of new firms surviving after 6 years, Stam and Wennberg (2009) evaluate the impact of R&D on the 6-year employment growth rate. R&D activities positively affect firm growth only in the subsamples comprising the highest decile (the "superstar-growth firms"), or high-tech firms.[3] Notably, the result is obtained by performing an inferential analysis on the subsample of high-growth firms and comparing the results with the outcome of a same analysis performed on the whole population (or a different sample) of firms. However, when growth is the dependent variable, estimating a model on a sample built on the basis of growth itself is dangerous: estimation strategies based on the truncation of the dependent variable "are doomed to failure for all the reasons so carefully laid out in Heckman's (1979) work on sample selection" (Koenker and Hallock 2001, p. 147). This is one of the reasons that has recently brought some researchers to adopt quantile regressions for investigating the heterogeneity of firm growth patterns. Quantile regressions show how an increased level of the independent variables (e.g. of R&D expenditure) corresponds to a new expected *conditional* distribution of the dependent variable (e.g. of firm growth rates) that is the distribution we expect for a sample of hypothetical individuals having the same new level of the independent variables.[4] Hölzl (2009) employs quantile regressions to discover that R&D intensity has a positive influence on firm 1-year growth rates in countries closer to the technology frontier, at all conditional quantiles (i.e. at all quantiles of the conditional distribution), and with higher coefficients at higher conditional quantiles. Goedhuys and Sleuwaegen (2010), in an innovation study conducted over 11 African countries, find a positive effect of

[2] A discussion of Ricardo's views on the issue can be found in Samuelson (1988).

[3] The authors mention that they are aware of issues regarding selection bias from firm exit, but were not able to control for attrition in their estimation given that it could be attributed to firm death or non-response to the survey, the latter being quite random.

[4] Henceforth, unless differently stated, the word "conditional distribution" will always mean "distribution conditional to the level of the independent variables". More details about quantile regressions, and the way we use them, are provided in Sect. 4.2, where the models we estimate are described.

product innovation on 3-year growth rates in high conditional quantiles, and a negative coefficient of process innovation at the 80th conditional quantile (the study does not employ any measure of R&D expenditure, but only dummy variables built for several innovation indicators). Finally, Segarra and Teruel (2014) use a two-step approach in their study on Spanish firms' 1-year growth rates. After uncovering the determinants of being a high-growth firm using a Probit model, they apply a quantile regression to examine the determinants of firm growth. They reveal diverse effects of internal and external R&D, where the former has a positive impact on the highest quantiles (above the 75th conditional quantile), while the latter positively increases conditional growth rates up to the median.

We build on the intuitions from this new branch of the literature, by using quantile regressions to study the influence of R&D on firm growth over an extended time horizon, and dealing with the firm exit issue arising from such extension. More in general, given that the existing empirical evidence on the link between R&D expenditure and employment growth presents a diverse set in terms of (1) the growth rate lag and (2) sample selection (survival, size, growth rate, and sectoral characteristics), and it is therefore difficult to compare the results across studies, our empirical strategy will address this matter directly by (1) computing employment growth rates at different lags, (2) allowing the estimated coefficients to be heterogeneous over the conditional distribution of the employment growth rates, (3) addressing the selection bias due to firm failure.

We must remind the reader that our analysis involves only firms having declared a positive R&D expenditure. In the next section, we will explain why the characteristics of our dataset have brought us to this decision. The comparison of our results with the findings in the previous literature must then take into account how the previous studies have dealt with the issue of zero R&D observations. Coad and Rao (2010), Segarra and Teruel (2014) (who, like us, adopt a logarithmic transformation of the R&D expenditure) and Klette and Griliches (2000) choose for the exclusion of observations with zero R&D.[5] Hall (1987) introduces a dummy variable equal to 1 when firms have no R&D expenditure and still keeps as a regressor the logarithm of R&D intensity (it is not clear which is the value of the latter regressor when R&D expenditure is equal to zero). Hall et al. (2008) have the same approach: not excluding the firms with R&D equal to zero (zero R&D employees, in this case) and using a dummy variable equal to 1 when firms do not perform R&D. Cohen and Levinthal (1989) perform two separate analyses, respectively, for the whole sample and for the subsample of firms with positive R&D. Brouwer et al. (1993), Leiponen (2005), Greenhalgh et al. (2001), Rammer et al. (2009), Stam and Wennberg (2009), Hölzl (2009) and Hölzl and Friesenbichler (2010) keep the zero-R&D observations in the analysis. The other innovation studies cited in this section do not employ any variable corresponding solely to R&D.

3 Data and variables

For our research, we use the data from the Community Innovation Survey (CIS) that refer to the Netherlands, and from the Business Register (*Algemeen Bedrijven Register*—ABR) provided by the Dutch statistical office (Statistics Netherland—CBS). The CIS is a firm-level survey conducted every 2 years in all EU member states (plus non-EU countries like Norway and Iceland), and the Business Register is a census of the whole Dutch firm population. We consider the six waves of the innovation survey conducted between 1996 and 2006 and match them with yearly data from the Business Register from 1996 to 2011. Although many firms report zero R&D in the CIS survey (as reported in Table 7 in the "Appendix", out of the initial 62,705 observations, we discard 31,650 due to missing information about total R&D, and 9,782 which report them as zero), in the final sample we choose to include only firms with positive R&D expenditure. First, we are not sure that the observed zeros truly reflect that firms decided not to invest in R&D. Indeed, small firms might report a null value due to their difficulty of assessing their R&D effort if they do not have a separate R&D department. Besides, in the third CIS wave (2000), missing observations are

[5] Segarra and Teruel (2014) also consider zero-R&D firms in the first part of their analysis on the determinants of being a HGF by the means of a dummy variable equal to 1 when firms have no R&D expenditure.

Footnote 5 continued

coded as zeros. Second, the additional variables we could use to explain the probability of having an observed R&D higher than zero (in the selection equation of a Heckman model) are available only for a subset of observations and are not homogeneous across CIS waves. We also remove from our database any observation with a ratio of R&D expenditure to turnover higher than one, or an employment growth rate higher than 2 (corresponding to more than 500 % relative growth). The cleaned data retains 20,770 observations from 13,236 firms. In the regressions, a reduced version of the database, in which double counting of the same firms is avoided, will be used when pooling the six waves into a unique cross section. We do so by keeping only the final observation for each firm.[6]

We computed R&D intensity as the ratio between the firm's R&D expenditure (survey variables *uitota* in 1996 and 1998 and *rtot* in the subsequent CIS waves) and turnover (survey variables *omztot96, omz98imp, turn, turn02, turn04 and turn06* for 1996, 1998, 2000, 2002, 2004 and 2006, respectively). We use a logarithmic transformation to obtain the variable $\overline{\mathrm{RD}}$ that will be used in the rest of the analysis as our measure of (transformed) observed R&D intensity. Table 1 summarizes the information regarding the distribution of the R&D to sales ratio (upper panel)[7] and of the $\overline{\mathrm{RD}}$ (lower panel) variables. Figure 1 (left) shows the (unconditional) distribution of $\overline{\mathrm{RD}}$ when pooling all the observations. Apart from the right-truncation in zero (due to our exclusion of firms having R&D expenditure higher than turnover), the distribution of $\overline{\mathrm{RD}}$ resembles a Gaussian, as evident from its negative skewness and low excess kurtosis (see also Fig. 1, left). Figure 1 (right) shows that if we condition on the firm's survival after 2 years, the distribution of $\overline{\mathrm{RD}}$ slightly differs for the group of exiting firms. If the support of the distribution is similar, the tails are slightly fatter on both sides. This would indicate that exiting firms have a more extreme R&D behaviour than surviving ones. If very low investment in R&D can weaken the firms' competitiveness and therefore its market share, overinvestment given the firms' internal resources, and the uncertainty regarding the success of the innovative process, can also lead to firm death.

The second variable of interest in our analysis is employment growth. Since we will be considering firm performance both in the short and medium terms, we compute our growth measure at different lags. If we name t each year in which the CIS survey has been conducted, the corresponding medium-term firm performance is computed as the firm growth between $t+1$ and $t+5$, where firm size is proxied by firm employment plus one, and the data on employment have been retrieved by matching the CIS data with the data of the Business Register (variable *wp_verslagjaar*). By matching with the Business Register, which contains yearly information on the whole population of firms registered for fiscal purposes in the Netherlands, we are able to check the survival of firms and to measure the growth rate of surviving firms, during the 5 years following the CIS survey wave in which the same firms were surveyed. Besides this 4-year growth rate ($k=4$), we also compute the 1-, 2- and 3-year growth rates as proxies of shorter-term performance.

To define firm growth for each firm i and year $t = 1996, 1998, 2000, 2002, 2004, 2006$ at lag $k = 1, 2, 3, 4$, we start from the expression of relative firm growth (subsequent to the R&D expenditure):

$$\mathrm{relgrowth}_{i,t}^{k} = \frac{\mathrm{size}_{i,t+1+k} - \mathrm{size}_{i,t+1}}{\mathrm{size}_{i,t+1}}$$

which can have values between -1 and $+\infty$, and we transform it in the following way:

$$g_{i,t}^{k} = \log(\mathrm{relgrowth}_{i,t}^{k} + 2) \tag{1}$$

Such measure of growth can take only values included between 0 and $+\infty$ (zero in case of exit) and will be the growth proxy used in the rest of our study. We choose to depart from previous studies on firm growth and R&D expenditure (Coad and Rao 2008, 2010; Klomp and Van Leeuwen 2001), and more generally the literature on firm growth distributions (Bottazzi and Secchi 2006) which consider the log size difference, for the following reason. For high positive growth rates, the log transformation applied to the relative growth rate (Eq. 1) makes it similar to the log

[6] All the regression results are robust to the use of the firms' first occurrence instead. Moreover, Tables 7 and 8 in the "Appendix" provide more information about the different steps of the cleaning procedure and the decomposition of the total number of observations in the different samples.

[7] A summary of the empirical stylized facts regarding R&D expenditure can be found in Klette and Kortum (2004).

Table 1 Descriptive statistics on R&D

Original data after cleaning				Without double counting			
Statistics on the ratio between R&D expenditure and turnover							
Quantiles		Mean	0.044	Quantiles		Mean	0.0460
0.01	0.000	Variance	0.009	0.01	0.000	Variance	0.010
0.05	0.001	Skewness	5.114	0.05	0.001	Skewness	4.902
0.10	0.002	Kurtosis	36.438	0.10	0.002	Kurtosis	32.958
0.25	0.005			0.25	0.005		
0.50	0.014			0.50	0.014		
0.75	0.040			0.75	0.040		
0.90	0.103			0.90	0.110		
0.95	0.182			0.95	0.199		
0.99	0.503	No. obs.	20,770	0.99	0.550	No. obs.	13,236
Statistics on R&D intensity (computed as logarithm of the ratio between R&D expenditure and turnover)							
Quantiles		Mean	−4.303	Quantiles		Mean	−4.319
0.01	−8.298	Variance	2.601	0.01	−8.377	Variance	2.756
0.05	−6.973	Skewness	−0.251	0.05	−7.039	Skewness	−0.231
0.10	−6.370	Kurtosis	3.510	0.10	−6.429	Kurtosis	3.499
0.25	−5.343			0.25	−5.401		
0.50	−4.255			0.50	−4.285		
0.75	−3.230			0.75	−3.207		
0.90	−2.273			0.90	−2.204		
0.95	−1.705			0.95	−1.616		
0.99	−0.687	No. obs.	20,770	0.99	−0.598	No. obs.	13,238

In the right part of the table, firms that were present in more than one survey year have been considered only for the last year

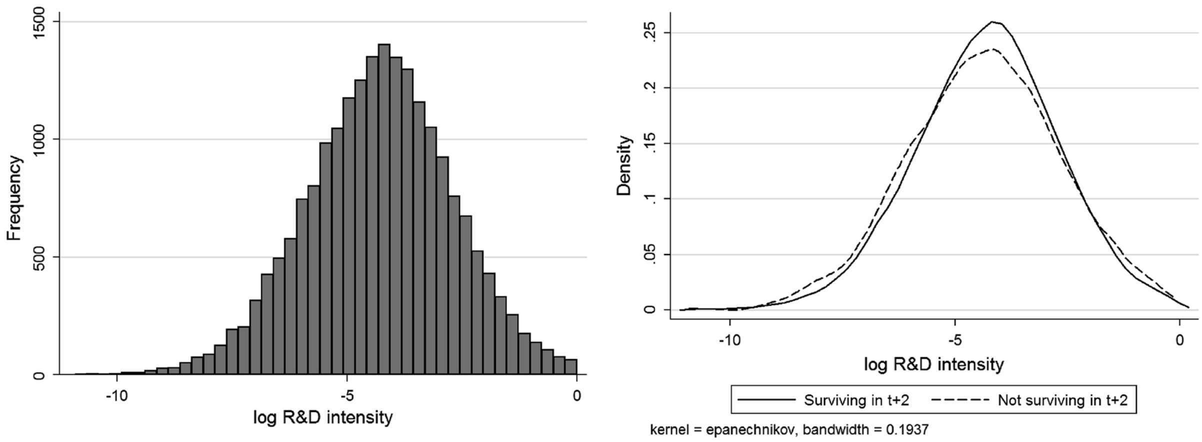

Fig. 1 Density plot of (transformed) observed R&D intensity, $\overline{\text{RD}}$. It is computed as the logarithm of R&D expenditure over turnover. Firms with R&D expenditure equal to zero have not been considered in the analysis. For values of R&D intensity below −11 (still included in the analysis), the density is too low to be shown in the *graph*. The *right plot* shows the kernel density of the same variable, conditional on survival after 2 years

difference growth rate: it allows to reduce the effects of heteroscedasticity on the econometric outcomes, by giving less weight to the extreme positive events (as also noted by Coad and Hölzl 2012). Instead, in the case of extreme negative events (exit), our measure is less affected by the endogenous truncation issue put forward by Capasso and Cefis (2012) than the log difference one.[8] This latter feature is of particular relevance since we are interested in the evaluation of performance changes in the medium term, and such longer term may affect the frequency and the magnitude of extreme (positive or negative) growth events.

A descriptive summary of the size and growth variables used in our analysis is reported in Table 2 and completed by Fig. 2. Figure 2 (left) shows that the resulting (unconditional) distribution of the 4-year growth rates (obtained when pooling all the observations and not considering exits) resembles a Laplace and looks symmetric in the body (mean and median values coincide). By construction, its left tail is truncated in zero, and its right tail is very long to include some episodes of outstandingly high growth. This is in line with the findings of Stanley et al. (1996) and Axtell (2001), who use a log size difference approximation of growth. The shorter-term growth rates share comparable characteristics: all growth rates present positive skewness and large excess kurtosis (see Table 2, lower panels). Note that if the length of the tails, as proxied by the value at the 99th percentile, is similar at all lags, short-term growth rates are characterized by lower variance, and higher skewness and kurtosis. Indeed, the distribution of short-term growth rates displays a higher peak with the same support as medium-term growth rates, as illustrated in Fig. 2 (right panel).

4 Methodology

4.1 Methodological issues

4.1.1 Controlling for firm survival

Of the 13,236 firms observed in the six CIS survey waves and matched with ABR data (including firms present in more than one wave), 3,357 have exited during the 5 years following the survey. Given the medium-term span on which we measure performance, the decision of balancing the panel, and thus exclude from the analysis the exiting firms, would result empirically into a strong reduction of the amount of data used, and theoretically into neglecting the influence that R&D (and in general the whole innovation process) has on firm survival, an influence already shown on similar data by Cefis and Marsili (2005).

We face two problems of variable left-limitation: the one of the dependent variable (firm growth) and the other of the independent variable of interest (R&D intensity). The typical way of dealing with such problems is through the limited variable regression models named Tobit, and in particular either the original Tobit model (Tobit type I, introduced by Tobin 1958) or its alternate version usually employed for correcting possible selection biases (Tobit type II, also known as Heckit, introduced by Heckman 1979, and homogenized in the Tobit framework by Amemiya 1984). The choice between Tobit type I and Tobit type II should be based on the assumptions made about the variable limitation: is the limit value observed for some individuals (the censored observations) deriving from the same process that causes the non-limit value for other individuals (the noncensored observations)? Rephrasing for our two cases of left-limitation, the question becomes respectively: "Are the firm exits from the market deriving from the same process that defines the growth of surviving firms?" and "Is the decision of declaring no R&D expenditure deriving from the same process that defines the amount of money spent on R&D by firms that declare an R&D expenditure?" We explain below how we will deal with the growth variable limitation; however, due to the issues with the R&D variable described at the beginning of the previous section, we choose to consider only positive R&D expenditure declarations in our final sample, excluding zeros from our analysis.

For the growth variable, we assume that firms exiting the market are firms that have experienced strong negative growth rates (relative growth rates lower than -100 %, i.e. values of our growth measure lower than zero). In other words, we assume that exit from the market and growth rates of surviving firms are governed by the same process (i.e. by the same relation with the independent variables). The natural consequence of our assumption is adopting a Tobit type I model for explaining exit and growth. We thus distance ourselves from the studies of Hall (1987), Evans (1987) and Brouwer et al. (1993). They instead choose a Tobit type II model, assuming that the decision to exit is governed by a different process than

[8] This particular point is explained in more detail in the "Appendix".

Table 2 Descriptive statistics on firm size and growth

Original data after cleaning				Without double counting			
Statistics on firm log size (computed as logarithm of firm employment plus one)							
Quantiles		Mean	4.274	Quantiles		Mean	3.999
0.01	1.099	Variance	1.725	0.01	1.099	Variance	1.766
0.05	2.303	Skewness	0.206	0.05	1.792	Skewness	0.266
0.10	2.708	Kurtosis	4.018	0.10	2.485	Kurtosis	3.963
0.25	3.401			0.25	3.135		
0.50	4.277			0.50	3.989		
0.75	5.037			0.75	4.796		
0.90	5.875			0.90	5.638		
0.95	6.447			0.95	6.252		
0.99	7.747	No. obs.	20,770	0.99	7.503	No. obs.	13,236
Statistics on 1-year growth rates, excluding exits							
Quantiles		Mean	0.701	Quantiles		Mean	0.682
0.01	0.300	Variance	0.156	0.01	0.214	Variance	0.020
0.05	0.547	Skewness	1.015	0.05	0.511	Skewness	1.152
0.10	0.616	Kurtosis	18.238	0.10	0.6	Kurtosis	14.787
0.25	0.682			0.25	0.679		
0.50	0.693			0.50	0.693		
0.75	0.716			0.75	0.714		
0.90	0.794			0.90	0.811		
0.95	0.877			0.95	0.908	No. exits	722
0.99	1.114	No. obs.	20,048	0.99	1.197	No. obs.	12,514
Statistics on 2-year growth rates, excluding exits							
Quantiles		Mean	0.699	Quantiles		Mean	0.694
0.01	0.154	Variance	0.026	0.01	0.102	Variance	0.032
0.05	0.46	Skewness	0.647	0.05	0.418	Skewness	0.589
0.10	0.551	Kurtosis	11.231	0.10	0.522	Kurtosis	9.929
0.25	0.651			0.25	0.64		
0.50	0.693			0.50	0.693		
0.75	0.744			0.75	0.744		
0.90	0.847			0.90	0.859		
0.95	0.94			0.95	0.964	No. exits	1,573
0.99	1.253	No. obs.	19,197	0.99	1.299	No. obs.	11,663
Statistics on 3-year growth rates, excluding exits							
Quantiles		Mean	0.698	Quantiles		Mean	0.689
0.01	0.091	Variance	0.034	0.01	0.065	Variance	0.042
0.05	0.416	Skewness	0.537	0.05	0.361	Skewness	0.489
0.10	0.514	Kurtosis	8.937	0.10	0.48	Kurtosis	7.866
0.25	0.627			0.25	0.609		
0.50	0.693			0.50	0.693		
0.75	0.764			0.75	0.763		
0.90	0.875			0.90	0.889		
0.95	0.981			0.95	1	No. exits	2,629
0.99	1.323	No. obs.	17,961	0.99	1.386	No. obs.	10,607

Table 2 continued

Original data after cleaning				Without double counting			
Statistics on 4-year growth rates, excluding exits							
Quantiles		Mean	0.693	Quantiles		Mean	0.682
0.01	0.087	Variance	0.041	0.01	0.065	Variance	0.048
0.05	0.375	Skewness	0.504	0.05	0.327	Skewness	0.447
0.10	0.428	Kurtosis	7.375	0.10	0.440	Kurtosis	6.633
0.25	0.606			0.25	0.587		
0.50	0.693			0.50	0.693		
0.75	0.773			0.75	0.772		
0.90	0.901			0.90	0.911		
0.95	1.013			0.95	1.030	No. exits	3,357
0.99	1.352	No. obs.	17,016	0.99	1.386	No. obs.	9,879

In the right part of the table, firms that were present in more than one survey year have been considered only for the last year. All growth rates are computed as logarithm of relative growth plus two

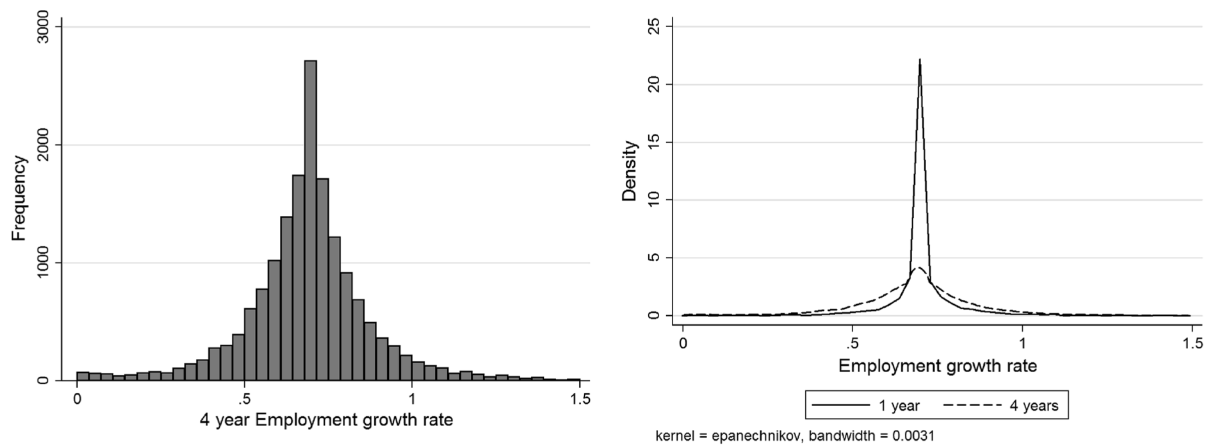

Fig. 2 Distribution of employment growth, excluding exits. It is computed as logarithm of relative growth plus two. The *left plot* shows the histogram of the 4-year growth rates, and the *right plot* shows the kernel density plot comparing the 4- to 1-year growth rates. For values above 1.5, the density is too low to be shown in the *graph*

low growth, and therefore must be modelled separately.[9]

4.1.2 On the usefulness of quantile regression analysis

Quantile regression methods have been introduced by Koenker and Bassett (1978) in order to overcome the "robustness to distributional assumptions" problem. Indeed, the authors explain that the least-squares estimator is very efficient if the analysed random variable is distributed according to a Gaussian, but its variance increases when considering alternative error distributions. In particular, the conditional mean and median fits can be quite different if the conditional density is asymmetric or due to the presence of outliers. Instead, other estimators of location put a reduced weight on extreme observations (for example, the α—trimmed mean simply removes them), thus "while making a small sacrifice of efficiency to the mean of the Gaussian distribution, are greatly superior

[9] Note that the sample selection correction is not found to be significant by Hall (1987) and Brouwer et al. (1993).

to the mean for non-Gaussian distributions" (Koenker and Bassett 1978, p. 36). The purpose of the quantile regression approach is then presented as an estimator which remains robust when the distribution of the variable under study is not known. Because the distribution of employment growth rates departs from the normality assumption, as illustrated in Fig. 2, we must consider the possibility that errors are not normally distributed, and therefore a robustness criterion is well adapted to the present study. Relatedly, one issue regarding the estimation of the Tobit model with least squares in our setting is its potential inconsistency in the case of a non-normal disturbance term. Unfortunately, the application of the censored quantile regression model introduced by Powell (1986) was not possible for practical reasons.[10]

In addition, this approach has other interesting attributes, as described by Buchinsky (1998). In particular, because the effect of the regressors is estimated at different locations of the conditional distribution (at different quantiles), the parameters defining the response of the dependent variable to changes in the independent variables can also differ. In our case, as discussed in Sect. 2, we expect the characteristics of conditionally high-growth firms to differ from the average. Understanding such heterogeneous response pattern is of crucial importance in terms of policy analysis and can help design more targeted policies supporting firm growth.

4.1.3 Direction of causality

We implicitly assume an ideal pattern linking, unidirectionally, R&D to innovation to productivity to employment growth. Of course, alternative approaches would be possible that consider at the same time three or more rings of the same chain, as in the multistep procedure by Crepon et al. (1998) or Hall et al. (2009), or that take into account multidirectional causation processes, as in Coad and Rao (2010) or Moneta et al. (2013). Although not explicitly considered here, the potential "feedback" effect of the influence of firm growth on R&D could also be important when the analysis of firm survival and performance is not confined to the short term.

4.2 Models

In what follows, we present the alternative models to be estimated. In particular, we will compare the impact of R&D intensity on firm growth when considering "the average effect on the average firm" (Model 1), when explicitly controlling for firm survival in a Tobit type I model (Model 2), or when the coefficients are estimated at different locations of the conditional growth rate distribution in a quantile regression model (Model 3). In all models, to avoid double counting of the same firms in the pooled cross section, for firms that were present in more than one survey wave, only the observations pertaining to the oldest wave are kept, thus reducing the number of observations from 20,770 to 13,236 (i.e. exactly the total number of firms present in the database after cleaning the data, see also Table 7 in the "Appendix"). Referring to firm i, lag k and period t, the dependent variable is observed firm growth $g_{i,t}^k$, computed as in Eq. 1, and the set of regressors is the $K \times 1$ vector $x_{i,t}$:

$$x_{i,t} = \Big[\overline{\mathrm{RD}}_{i,t} \;\; \mathrm{size}_{i,t} \;\; \mathrm{group}_i \;\; \overline{\mathrm{RD}}_{i,t} * \mathrm{size}_{i,t} \;\; \overline{\mathrm{RD}}_{i,t} * \mathrm{group}_i \;\; \mathrm{logsize}_{i,t} * \mathrm{group}_i \;\; \mathrm{sector}_i \;\; \mathrm{wave}_t\Big] \tag{2}$$

where $\mathrm{size}_{i,t}$ is the logarithm of firm employment plus one; $\overline{\mathrm{RD}}_{i,t}$ is the observed R&D intensity defined as in Sect. 3; group_i is a dummy variable taking value equal to 1 if the firm is part of a bigger industrial group; the interaction terms of the previous three variables are included as well. Besides, sector and time dummy variables are introduced: sector_i is a vector of 51 dummy variables, each one associated with a given 2-digit sector, assuming value equal to 1 if the firm belongs to the given sector and zero otherwise, and wave_t is a vector of dummy variables, each one associated with the survey wave to which the observation belongs.

[10] Indeed, we are limited in the types of softwares we can use on our data (accessed through a server managed by the CBS), and the algorithm of the Stata command *clad* modelling the censored least absolute deviations estimator with bootstrapped standard errors did not converge. Powell (1986)'s quantile estimator, though consistent, is computationally complex and inefficient. Therefore, quantile regression models will be estimated separately when including the exit cases (as firms with growth rates equal to 0) and when considering only surviving firms.

4.2.1 Model 1: The linear regression model

Model 1 is a pooled OLS regression estimating the conditional mean function linearly linking the dependent and independent variables, as follows:

$$g^k_{i,t} = \alpha + \beta x_{i,t} + u_{i,t} \tag{3}$$

4.2.2 Model 2: Tobit type I model for growth

We assume that a latent variable is, for each firm, linearly related to the independent variables and is linked to the observed firm growth $g^k_{i,t}$, as in the following:

$$y_{i,t} = \alpha + \beta x_{i,t} + u_{i,t}$$
$$g^k_{i,t} = \begin{cases} y_{i,t}, & \text{if} \quad y_{i,t} > 0 \\ 0, & \text{if} \quad y_{i,t} \leq 0 \end{cases}$$

This is tantamount to saying that exiting firms (i.e. firms for which $g^k_{i,t} = 0$) are firms for which the latent variable assumes nonpositive values.

4.2.3 Model 3: The quantile regression model

The quantile regression model describes the conditional quantile function linking the dependent and independent variables. It is estimated via least squares. Following Koenker and Bassett (1978), the linear regression model described by Eq. (3) can be expressed as:

$$g^k_{i,t} = \alpha_\theta + \beta_\theta x_{i,t} + u_{\theta_{i,t}}$$

where $0 < \theta < 1$ represents the share of the population with a growth rate $g^k_{i,t}$ below the quantile at θ. The θth conditional quantile given $x_{i,t}$ is then $\text{Quant}_\theta(g^k_{i,t}|x_{i,t}) = \alpha_\theta + \beta_\theta x_{i,t}$. It is determined by the set of parameters (to be estimated) α_θ and β_θ and a specific value of the regressors. The distribution of the error term $u_{\theta_{i,t}}$ is unspecified, provided it satisfies the quantile restriction $\text{Quant}_\theta(u_{\theta_{i,t}}|x_{i,t}) = 0$.

The parameters are then computed as the solutions to the minimization of a weighted sum of absolute residuals (Koenker and Hallock 2001) also called the *criterion function*:

$$\min_{\alpha_\theta,\beta_\theta} \left\{ \sum_{i,g^k_{i,t} \leq \alpha_\theta + \beta_\theta x_{i,t}} \theta |g^k_{i,t} - \alpha_\theta - \beta_\theta x_{i,t}| + \sum_{i,g^k_{i,t} > \alpha_\theta + \beta_\theta x_{i,t}} (1-\theta)|g^k_{i,t} - \alpha_\theta - \beta_\theta x_{i,t}| \right\}$$

In that case, the quantile θ represents a weighting factor between the left and right terms, i.e. the sum of all negative residuals (the observations below the quantile, i.e. slower growing firms) and all positive residuals (the observations above the quantile, i.e. faster growing firms), respectively. Note that the median regression (also known as Least Absolute Deviation, LAD) attributes equal weights to both terms. This allows to realize that all observations are used in the estimation of the different quantile parameters β_θ, but they differ by the weights they are given in each regression (for instance, faster growing firms are given a higher weight at higher quantiles).

Finally, in order to assess the effect of selection on our results besides the use of a censored regression model (Model 2), for Models 1 and 3 we run two different sample specifications (with or without exiting firms, that is, with growth rate equal to 0).

5 Results

The regression results obtained for the three models and the four growth lags are shown in Tables 3, 4, 5 and 6.[11] In addition, to facilitate the comparisons across quantiles and growth rate lags, the quantile regression coefficients for the main variable of interest ($\overline{\text{RD}}$), along with the 10 % significance confidence bands, are reported in Figs. 3 and 4.

5.1 Asymmetric effects

With the linear regression model (Model 1), we estimate the average firm growth given the firm's

[11] All regressions were run by using the Stata software package. In particular, for Model 1, we estimate robust standard errors, for Model 2, the *tobit* function has been used with the option suffix "ll(0) vce(bootstrap, rep(500))" (bootstrapped standard errors, 500 replications); and, for Model 3, the *bsqreg* function has been supplemented with the option suffix "reps(500) seed(100)" (bootstrapped standard errors, 500 replications, setting the same seed to all quantile regression estimations).

Table 3 Regression results, 1-year growth rate $(t+1; t+2)$

Including exits	OLS	Tobit	Q10	Q25	Q50	Q75	Q90
$\overline{\text{RD}}$	−0.005	−0.006	−0.012	0.001	0.000	−0.002*	0.011*
	(0.003)	(0.004)	(0.010)	(0.001)	(0.002)	(0.001)	(0.006)
Size	−0.006	−0.006	−0.005	−0.005**	0.000	0.002**	−0.021***
	(0.004)	(0.004)	(0.014)	(0.002)	(0.001)	(0.001)	(0.005)
Group	−0.021	−0.024	−0.093**	−0.022*	0.000	0.006	0.029
	(0.016)	(0.016)	(0.043)	(0.013)	(0.008)	(0.006)	(0.049)
$\overline{\text{RD}}$ ∗ size	0.001	0.001	0.003	−0.000	0.000	0.000	−0.002
	(0.001)	(0.001)	(0.003)	(0.002)	(0.000)	(0.000)	(0.001)
$\overline{\text{RD}}$ ∗ group	−0.001	−0.001	−0.002	0.000	−0.000	0.000	−0.000
	(0.002)	(0.003)	(0.007)	(0.002)	(0.000)	(0.001)	(0.008)
Size ∗ group	0.001	0.001	0.014	0.006***	−0.000	−0.002	−0.006
	(0.003)	(0.003)	(0.009)	(0.002)	(0.001)	(0.001)	(0.005)
Constant	0.687***	0.682***	0.222	0.672***	0.693***	0.738***	1.011***
	(0.028)	(0.030)	(0.164)	(0.036)	(0.004)	(0.039)	(0.083)
No. obs.	13,236	13,236	13,236	13,236	13,236	13,236	13,236
Censored		722					
Uncensored		12,514					

Excluding exits	OLS	Q10	Q25	Q50	Q75	Q90
$\overline{\text{RD}}$	−0.001	−0.000	0.000	−0.000	−0.003**	0.011**
	(0.002)	(0.006)	(0.002)	(0.000)	(0.001)	(0.005)
Size	−0.006**	0.001	−0.003	−0.000	0.002*	−0.022***
	(0.003)	(0.008)	(0.003)	(0.000)	(0.001)	(0.005)
Group	0.008	−0.053**	−0.001	0.000	0.014*	0.047*
	(0.011)	(0.026)	(0.037)	(0.000)	(0.008)	(0.024)
$\overline{\text{RD}}$ ∗ size	−0.000	0.000	−0.000	−0.000	0.001*	−0.002*
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)
$\overline{\text{RD}}$ ∗ group	0.001	−0.002	0.001	0.000	0.000	0.002
	(0.002)	(0.004)	(0.002)	(0.000)	(0.001)	(0.003)
Size ∗ group	−0.001	0.010**	0.002	0.000	−0.003***	−0.008**
	(0.002)	(0.005)	(0.007)	(0.000)	(0.001)	(0.004)
Constant	0.748***	0.599***	0.695***	0.693***	0.734***	1.019***
	(0.019)	(0.051)	(0.041)	(0.006)	(0.019)	(0.076)
No. obs.	12,514	12,514	12,514	12,514	12,514	12,514

Pooled cross-sectional models, keeping firms' last observation when removing duplicates. Dummy variables relating to 2-digit sectors and to the cross-sectional waves have been included in all models

Standard errors in parentheses below the parameter estimates

* Significant at 10 %, ** significant at 5 %, *** significant at 1 %

R&D intensity. Instead, with the quantile regression model, we can infer the different conditional quantiles of firm growth when the R&D intensity is modified. Contrary to the linear regression model which reports mean shifts of the conditional growth distribution when the independent variables change, the quantile

Table 4 Regression results, 2-year growth rate $(t+1; t+3)$

Including exits	OLS	Tobit	Q10	Q25	Q50	Q75	Q90
$\overline{\mathrm{RD}}$	−0.005	−0.007	−0.013	−0.009	0.000	0.002	0.020
	(0.005)	(0.005)	(0.010)	(0.006)	(0.004)	(0.003)	(0.013)
Size	−0.027***	−0.029***	−0.063***	−0.023**	0.000	−0.013***	−0.047***
	(0.006)	(0.006)	(0.015)	(0.010)	(0.014)	(0.004)	(0.007)
Group	−0.044**	−0.049*	−0.296***	−0.069**	−0.000	−0.016	−0.003
	(0.021)	(0.026)	(0.075)	(0.029)	(0.006)	(0.019)	(0.047)
$\overline{\mathrm{RD}} *$ size	0.001	0.001	0.000	0.001	−0.000	−0.000	−0.004***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
$\overline{\mathrm{RD}} *$ group	0.003	0.003	0.013	0.003	−0.000	−0.000	0.005
	(0.003)	(0.004)	(0.008)	(0.005)	(0.001)	(0.002)	(0.004)
Size $*$ group	0.010**	0.010*	0.063***	0.018***	0.000	0.001	0.005
	(0.005)	(0.006)	(0.015)	(0.007)	(0.002)	(0.003)	(0.007)
Constant	0.696***	0.682***	0.296***	0.616***	0.693***	0.820***	1.087***
	(0.036)	(0.041)	(0.107)	(0.086)	(0.042)	(0.031)	(0.083)
No. obs.	13,236	13,236	13,236	13,236	13,236	13,236	13,236
Censored		1,573					
Uncensored		11,663					
Excluding exits	**OLS**		**Q10**	**Q25**	**Q50**	**Q75**	**Q90**
$\overline{\mathrm{RD}}$	0.002		−0.011	0.002	0.000	0.005	0.022***
	(0.003)		(0.007)	(0.006)	(0.000)	(0.003)	(0.007)
Size	−0.019***		−0.010	−0.013**	0.000	−0.015***	−0.047***
	(0.004)		(0.010)	(0.006)	(0.000)	(0.004)	(0.007)
Group	−0.013		−0.042	−0.030	−0.000	0.003	−0.002
	(0.015)		(0.033)	(0.023)	(0.000)	(0.014)	(0.026)
$\overline{\mathrm{RD}} *$ size	−0.001		0.000	−0.001	0.000	−0.001	−0.004***
	(0.001)		(0.002)	(0.001)	(0.000)	(0.001)	(0.001)
$\overline{\mathrm{RD}} *$ group	0.003		0.008	0.002	−0.000	0.001	0.002
	(0.002)		(0.005)	(0.003)	(0.000)	(0.002)	(0.004)
Size $*$ group	0.007**		0.019**	0.011**	−0.000	−0.001	0.004
	(0.003)		(0.008)	(0.004)	(0.000)	(0.003)	(0.005)
Constant	0.791***		0.557***	0.690***	0.693***	0.840***	1.106***
	(0.024)		(0.071)	(0.041)	(0.007)	(0.025)	(0.073)
No. obs.	11,663		11,663	11,663	11,663	11,663	11,663

Pooled cross-sectional models, keeping firms' last observation when removing duplicates. Dummy variables relating to 2-digit sectors and to the cross-sectional waves have been included in all models

Standard errors in parentheses below the parameter estimates

* Significant at 10 %, ** significant at 5 %, *** significant at 1 %

regression model can capture central location shifts (the median fit), or shape shifts (off-median fits). We comment on these elements below.

The conditional mean (Model 1) and conditional median (Model 3, 50th percentile) results do not assign particular value to $\overline{\mathrm{RD}}$,[12] with the exception of a positive coefficient in the conditional mean (OLS)

[12] Notice in Figs. 3 and 4 the smaller standard error at the median, as also found in Coad (2007).

Table 5 Regression results, 3-year growth rate $(t+1; t+4)$

Including exits	OLS	Tobit	Q10	Q25	Q50	Q75	Q90
$\overline{\text{RD}}$	−0.002	−0.003	−0.000	0.001	−0.001	−0.001	0.012*
	(0.006)	(0.007)	(0.000)	(0.008)	(0.007)	(0.009)	(0.006)
Size	−0.029***	−0.034***	0.000	−0.043***	−0.010**	−0.016**	−0.043***
	(0.007)	(0.008)	(0.000)	(0.012)	(0.005)	(0.006)	(0.006)
Group	−0.109***	−0.137***	−0.000	−0.282***	−0.025	−0.046*	−0.003
	(0.024)	(0.032)	(0.000)	(0.044)	(0.057)	(0.024)	(0.028)
$\overline{\text{RD}} *$ size	0.001	0.001	0.000	0.001	0.000	0.000	−0.002*
	(0.001)	(0.002)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)
$\overline{\text{RD}} *$ group	−0.002	−0.003	0.000	−0.008	−0.002	−0.001	0.001
	(0.004)	(0.005)	(0.000)	(0.007)	(0.009)	(0.005)	(0.004)
Size * group	0.016***	0.019***	0.000	0.040***	0.003	0.007*	0.002
	(0.005)	(0.006)	(0.000)	(0.010)	(0.007)	(0.004)	(0.005)
Constant	0.701***	0.683***	0.000	0.576***	0.734***	0.829***	1.144***
	(0.041)	(0.048)	(0.000)	(0.148)	(0.041)	(0.049)	(0.071)
No. obs.	13,236	13,236	13,236	13,236	13,236	13,236	13,236
Censored		2,629					
Uncensored		10,607					

Excluding exits	OLS	Q10	Q25	Q50	Q75	Q90
$\overline{\text{RD}}$	0.001	−0.000	0.001	−0.001	0.003	0.010
	(0.004)	(0.009)	(0.020)	(0.001	(0.005)	(0.008)
Size	−0.020***	−0.011	−0.004	−0.001	−0.020***	−0.043***
	(0.005)	(0.011)	(0.045)	(0.001)	(0.005)	(0.008)
Group	−0.017	−0.029	−0.003	0.000	−0.017	0.019
	(0.018)	(0.039)	(0.026)	(0.003)	(0.021)	(0.036)
$\overline{\text{RD}} *$ size	−0.001	−0.002	−0.000	0.000	−0.000	−0.002
	(0.001)	(0.002)	(0.009)	(0.000)	(0.001)	(0.002)
$\overline{\text{RD}} *$ group	0.001	0.003	0.001	−0.000	0.000	−0.001
	(0.003)	(0.007)	(0.013)	(0.001)	(0.003)	(0.005)
Size * group	0.007*	0.008	0.002	−0.000	0.004	−0.003
	(0.004)	(0.009)	(0.021)	(0.001)	(0.004)	(0.006)
Constant	0.805***	0.463***	0.670***	0.717***	0.878***	1.176***
	(0.030)	(0.079)	(0.119)	(0.013)	(0.046)	(0.074)
No. obs.	10,607	10,607	10,607	10,607	10,607	10,607

Pooled cross-sectional models, keeping firms' last observation when removing duplicates. Dummy variables relating to 2-digit sectors and to the cross-sectional waves have been included in all models

Standard errors in parentheses below the parameter estimates

* Significant at 10 %, ** significant at 5 %, *** significant at 1 %

regression of the 4-year growth rate (Table 6). Because such result is not found at the median, and the distribution of our dependent variable presents fat tails (see Table 2, lowest panel), we can infer that an important role is played by extreme (positive or negative) events of growth.

Indeed, the quantile regression results indicate that the effect of a higher R&D intensity has a larger

Table 6 Regression results, 4-year growth rate $(t+1; t+5)$

Including exits	OLS	Tobit	Q10	Q25	Q50	Q75	Q90
$\overline{\text{RD}}$	0.002	0.001	−0.000	0.007	0.003	0.004	0.016**
	(0.006)	(0.008)	(0.000)	(0.008)	(0.005)	(0.005)	(0.007)
Size	−0.037***	−0.045***	−0.000	−0.079***	−0.029***	−0.024***	−0.047***
	(0.007)	(0.008)	(0.000)	(0.009)	(0.006)	(0.006)	(0.007)
Group	−0.135***	−0.176***	−0.000	−0.519***	−0.082***	−0.059***	−0.035
	(0.025)	(0.034)	(0.000)	(0.051)	(0.025)	(0.023)	(0.029)
$\overline{\text{RD}} * \text{size}$	0.000	0.001	0.000	0.000	−0.001	−0.000	−0.002
	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
$\overline{\text{RD}} * \text{group}$	−0.004	−0.006	0.000	−0.007	−0.001	−0.003	−0.003
	(0.004)	(0.005)	(0.000)	(0.008)	(0.004)	(0.003)	(0.005)
Size * group	0.017***	0.021***	0.000	0.079***	0.014***	0.009**	0.003
	(0.005)	(0.007)	(0.000)	(0.009)	(0.005)	(0.004)	(0.006)
Constant	0.665***	0.634***	0.000	0.519***	0.746***	0.857***	1.115***
	(0.042)	(0.058)	(0.000)	(0.100)	(0.038)	(0.031)	(0.072)
No. obs.	13,236	13,236	13,236	13,236	13,236	13,236	13,236
Censored		3,357					
Uncensored		9,879					

Excluding exits	OLS	Q10	Q25	Q50	Q75	Q90
$\overline{\text{RD}}$	0.008*	0.009	0.002	−0.001	0.011**	0.019**
	(0.005)	(0.008)	(0.007)	(0.002)	(0.005)	(0.008)
Size	−0.025***	−0.014	−0.014	−0.006	−0.026***	−0.051***
	(0.005)	(0.010)	(0.009)	(0.008)	(0.007)	(0.008)
Group	−0.033*	−0.071	−0.031	−0.000	−0.011	−0.013
	(0.020)	(0.043)	(0.026)	(0.035)	(0.025)	(0.039)
$\overline{\text{RD}} * \text{size}$	−0.002*	−0.003	−0.001	0.000	−0.002	−0.003*
	(0.001)	(0.002)	(0.002)	(0.000)	(0.001)	(0.002)
$\overline{\text{RD}} * \text{group}$	−0.001	−0.003	0.002	0.001	−0.001	−0.005
	(0.003)	(0.009)	(0.005)	(0.002)	(0.005)	(0.006)
Size * group	0.008*	0.012	0.010*	0.002	−0.017	−0.000
	(0.004)	(0.009)	(0.006)	(0.008)	(0.076)	(0.007)
Constant	0.809***	0.499***	0.575***	0.724***	0.905***	1.201***
	(0.031)	(0.079)	(0.050)	(0.046)	(0.044)	(0.075)
No. obs.	9,879	9,879	9,879	9,879	9,879	9,879

Pooled cross-sectional models, keeping firms' last observation when removing duplicates. Dummy variables relating to 2-digit sectors and to the cross-sectional waves have been included in all models

Standard errors in parentheses below the parameter estimates

* Significant at 10 %, ** significant at 5 %, *** significant at 1 %

positive impact on the higher quantiles of firm growth. Drawing on Hao and Naiman (2007), we provide the following interpretation. Because the estimated coefficients of the impact of R&D on firm growth are positive (when significant) at higher quantiles, and not significant at low values,[13] we can infer that the predicted values are clustered for low levels of R&D

[13] With one exception, see the discussion about the 75th percentile 1-year growth rate below.

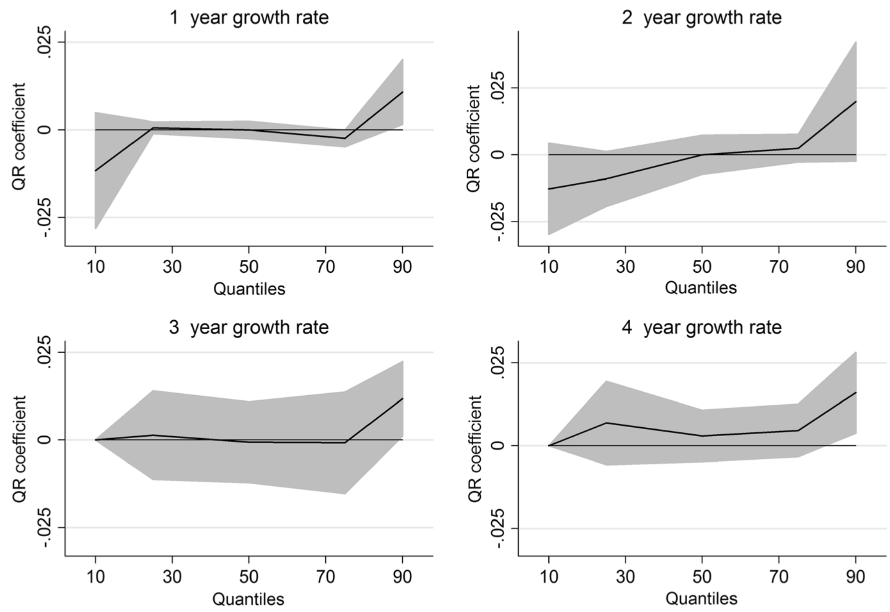

Fig. 3 Quantile regression results. Including exiting firms

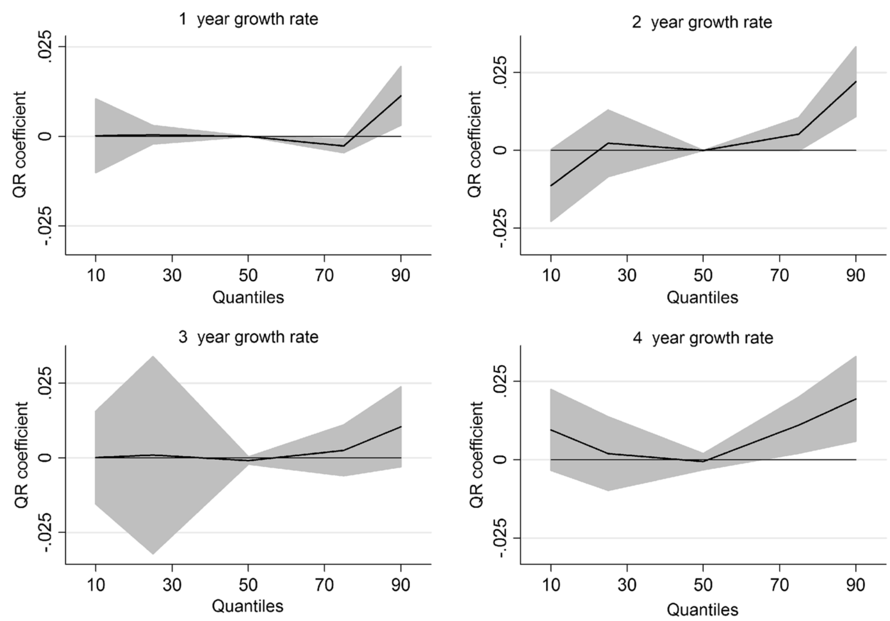

Fig. 4 Quantile regression results. Excluding exiting firms

intensity, but deviate more at higher levels. In other words, at high levels of R&D (given the level of the other independent variables), the right tail of the conditional growth rate distribution is fatter, that is, the successful firms are placed further from the other ones. Thus, a higher R&D does not seem to influence average growth nor to limit the unsuccessful events, but it creates more extreme successful events.

Note that the evolution of coefficients when increasing the quantiles is not linear.[14] For example,

[14] In order to understand more precisely what happens at high quantiles, we also compute the coefficients at intermediate locations (specifically, at the 80th, 85th and 95th quantiles), but do not report the results in the tables. They are available from the authors upon request.

standing out from the other results, we report a negative impact of $\overline{\mathrm{RD}}$ on the 1-year growth rate at the 75th percentile (Table 3). As also seen in Figs. 3 and 4, there is a trough in the line representing the coefficients when increasing the quantiles: at the 80th and 85th percentiles the estimated coefficient is negative but not significant, and turns positive at the 90th and 95th percentiles.[15] This would indicate a particular effect of R&D on the *shape* of the conditional firm growth distribution, more pronounced in the short term. A negative coefficient at the 75th percentile coupled with a positive one at the 90th percentile implies a larger divide that is perceivable between the body of the conditional firm growth distribution and its right tail. A tentative economic explanation would be: high levels of R&D entail high short-term costs which can even lower growth for all the firms (the majority) which are not able to translate the R&D investment into the exploitation of technological opportunities. Instead, top ("superstar") high-growth firms are the winners from the innovation game and manage to take full advantage of their opportunity set, thanks to their accumulated knowledge resources.

5.2 Selection effects

With respect to Model 1 (OLS), the parameters estimated according to the Tobit model are higher in magnitude, especially when it comes to longer-lag growth rates, thus correcting for the biased results obtained when the censored and uncensored observations are treated equally. Since we cannot apply the censored quantile regression model by Powell (1986), we try to infer the importance of the selection bias on the conditional quantile coefficients by other means, simply including or not the censored observations in the sample. After this process, we have to keep in mind that, when included in the analysis, the exit cases will represent low quantiles of the conditional growth distribution for any given level of R&D. Analogously, a 95 % quantile when including exits in the analysis may correspond, say, to a 90 % quantile when not including them. Such technical artefact may explain the fact that, when excluding the exiting firms, the positive impact of $\overline{\mathrm{RD}}$ for the 2- and 4-year growth rates at high quantiles is more pronounced (it becomes significant at the 90th percentile in the former case, cf. Table 4, and at the 75th percentile in the latter, cf. Table 6). This actually confirms our results in the entire sample, since, by construction, firms in the top percentiles in the overall sample are downgraded to a lower position in the distribution in the restricted sample.[16] However, the opposite is observed for the 3-year lag at the 90th percentile: a significant positive effect is found only when including exits. This result cannot be attributed to merely technical elements. In this particular case of 3-year growth rates, $\overline{\mathrm{RD}}$ is more important to explain survival than differences in growth performances among surviving firms.

5.3 Effects over time

Results are very robust across growth lags, with two exceptions. First, we observe a negative coefficient at the 75th percentile in the very short term, as discussed above. Second, if the quantile regression coefficients have similar magnitude, they sometimes differ in terms of significance level. Although the standard errors for the shorter growth rates are relatively smaller (as expected given the characteristics of the firm growth distributions at different lags, see Table 2), the estimations are more significant when moving from the short to the medium term. Recall that the influence of R&D that we measure is meant to be not only on growth after survival, but also on the probability of survival itself. In particular, the positive impact of $\overline{\mathrm{RD}}$ reaches a larger share of the conditional growth rate distribution in the medium term; the share of "winners" from the innovation game is expanded. As put forward by the literature on new product development time (see for e.g. Griffin 2002), those may include both the investors who embarked in more ambitious innovation projects, as well as the ones who suffered delays in the realization of their less ambitious ones.

[15] Although the estimated coefficient is higher at the 95th percentile with respect to the 90th, it is not significant due to a larger standard error.

[16] Indeed, the influence of $\overline{\mathrm{RD}}$ on the 2-year growth rate at the 95th percentile in the sample including exits is positive and significant. For similar reasons, the standard error and coefficients at the 10th percentile (when including exits, Fig. 3) are null in the medium term, because more than 10 % of observations are censored.

Regardless of these small differences, such convergence across time lags might seem at odds with the intuition and theoretical representation of the length of the innovation process. Still, this finding is in line with the existing heterogeneity in the new product development time across firms' organizational characteristics, types of R&D projects and sectors (Griffin 1997a, 2002).

5.4 Control variables and interaction effects

When significant, initial size (taken in logs) is negatively correlated with future firm growth, in line with the literature (since Hymer and Pashigian 1962). Belonging to a group seems also to exert a significant negative effect on growth. The interactions effects with $\overline{\mathrm{RD}}$ are rarely significant: only at the 90th quantile (Model 3) do we observe a negative interaction effect of R&D intensity with size: a higher $\overline{\mathrm{RD}}$ further develops the negative impact of size on the growth of the top firms, but it represents <10 % of the overall effect.

6 Conclusion

Our results expand previous findings on the relation between R&D expenditure and employment growth in several ways. With a focus on R&D investors, our study provides evidence on the heterogeneity in the returns to R&D on employment growth and survival between firms and over time.

First, our analysis shows that having a higher R&D intensity exerts a positive influence on firm employment. However, this influence is largely asymmetric as it appears only when considering high quantiles of the conditional growth rate distribution. An increase in the R&D intensity will make a high-growth firm deviate upward in its performance path, where performance is meant to be not only growth after survival, but also the probability of survival itself. Yet, a higher R&D intensity does not seem to influence average growth nor to limit the unsuccessful events. Second, we observe that the effects in the short and medium terms (5 years after the investment) generally converge. Indeed, the R&D variable captures all types of innovative projects and processes, with short- to medium-term impacts on firm performance. Further research is needed to disentangle the respective roles of organizational, project and industry characteristics in explaining the heterogeneity in the delays between the R&D investment and its impact on firm growth. Still, confirming the qualitative assessment in previous studies (Rothwell 1994; Coad and Rao 2010), shortening product development time presents some shortcomings such as higher costs which can even lower growth for all the firms (the majority) which are not able to translate the R&D investment into the exploitation of technological opportunities. Instead, if evaluating the returns to R&D in the medium term does not increase the impact in terms of magnitude, it expands the share of "winners", those who embarked in more ambitious innovation projects, and succeeded. Third, the effect that a higher R&D intensity exerts on firm survival cannot be ignored, especially when using firm-level analyses to predict the aggregate outcome of innovation policies at regional or country scale.

Summing up, once a firm invests in R&D, a higher investment makes the firm more likely to have a very good performance, but not less likely to have a bad performance. In the short term, the average effect of R&D intensity, which is the effect traceable by means of an OLS regression, is not significant. Instead, over a medium term (4-year growth rates) and when not considering exits, the positive influence of R&D on good performers is so strong that even an OLS estimation provides a significant coefficient for the R&D variable. Indeed, in this case, such a big portion of the right tail of the growth rate conditional distribution (including the 75th quantile) is shifted rightwards by the increase in R&D, that it causes an appreciable average effect. Without employing quantile regressions, such details about the relation between R&D and firm growth would not emerge. For instance, Stam and Wennberg (2009) find a positive medium-term influence of R&D within a high-growth firm subsample (i.e. for high "unconditional" quantiles of the firm growth rate distribution) and not for the whole sample, while we find a positive medium-term effect for "conditional" high-growth quantiles. In other words, Stam and Wennberg (2009) show that, among the firms that perform best within the whole sample, a higher R&D investment raises the probability of a better performance, while this is not the case for the rest of the firm population. Instead, we show that, in general, once the R&D investment is positive, a higher level of R&D intensity makes good performances better (where the "good" performance is defined "good" with respect to the given level of R&D). Roughly speaking, the "best performance" within a group of firms with low R&D is worse than the "best performance" within a group of firms with higher R&D. This relation holds also when the first "best performance" is not good enough to qualify as "high growth", while the second one is. In other words, the increase in R&D can make possible that the "best performers" belong to the group of "high-growth" firms, i.e. to the high quantiles of the "unconditional" growth distribution (the high quantiles of the observed distribution of growth rates for the whole sample, without conditioning on the level of R&D). Therefore, not only a higher R&D has a positive effect on high growers, but it allows a higher number of firms to become high growers.

Finally, our results differ from Hölzl (2009) in that he finds, in Continental Europe and in the short term, significant positive coefficients even for low conditional quantiles. The difference can be due to the inclusion of zero-R&D firms in the sample used by Hölzl (2009). By merging his results with ours, we can infer that (in a country close to the technology frontier) investing in R&D reduces the amount of bad performances; however, once the R&D intensity is positive, a further increase in the R&D intensity does not reduce the likelihood of bad performances.

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Appendix

Comparing growth rate measures

A variety of proxies have been used in studies concerning firm growth. Besides relative or absolute growth measures, the most popular measures are the Birch index (Birch 1981, 1987), which combines relative and absolute growth, and the log size difference. The Birch index has been used especially in studies interested in fast growing firms (Almus 2002; Hölzl 2009; Hölzl and Friesenbichler 2010), since it weighs proportional growth by the absolute change in the number of employees. For a size proxy x, the growth rate g of firm i, between periods t and $t-1$, is computed as:

$$g_{i,t} = (x_{i,t} - x_{i,t-1})\left(\frac{x_{i,t}}{x_{i,t-1}}\right)$$

It therefore gives more importance to large positive changes in firm size.[17] The log size difference has been chosen in the literature on firm growth and R&D expenditure (Coad and Rao 2008, 2010; Klomp and Van Leeuwen 2001), and more generally in the literature on firm growth distributions (Bottazzi and Secchi 2006). This measure allows to approximate proportional growth while reducing the importance of outliers (with large positive growth rates) and is computed as: $g_{i,t} = \log x_{i,t} - \log x_{i,t-1}$.

We choose to depart from these studies for two reasons. First, the approximation of the relative growth process by a log size difference is possible for a limited range of values. For instance, consider a number a; we know, by first order Taylor expansion around zero, that $\log(1+a) \approx a$ for small a. Note that the expression is not valid for values of a close to -1 or larger or equal than 1. Therefore, log size difference is a correct approximation of relative growth for values below 1 and not too close to -1. Outside of this range (in the case of extreme growth events), they are not similar.

A second characteristic of log size differences, as proxy for growth rates, has been put forward by Capasso and Cefis (2012) and involves the issue of endogenous truncation of the growth rate distribution: firms cannot have less than zero employees. When considering log size difference as a measure of growth

[17] This characteristic makes the Birch index particularly suitable for the study of high positive growth events, while this feature might not be considered of value for other research questions. This points to the fact that there is no universally best growth measure; the choice of the appropriate indicator may depend on the problem under question, the level of data disaggregation, the industry considered, or the time span of interest.

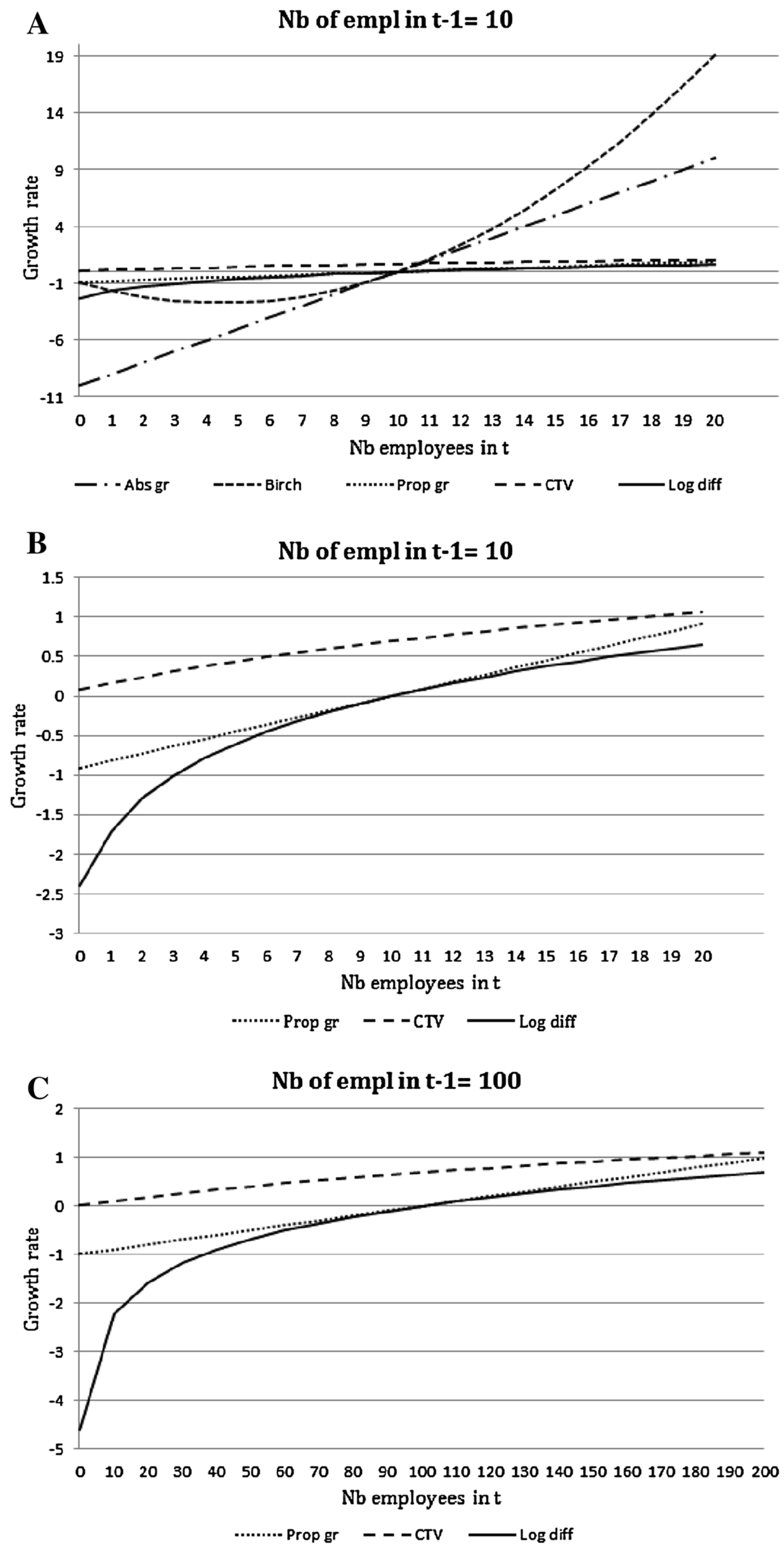

Fig. 5 Comparing growth rates measures. **a** We show the 1-year growth rate (measured on the vertical axis) of a firm having 10 employees in period $t-1$, and a number of employees ranging from 0 to 20 (measured on the horizontal axis) in the following period t, for five different growth indicators: absolute growth (Abs. gr), the Birch index (Birch), proportional growth (Prop), our measure (CTV) and log size difference (Log diff). **b** We do the same exercise as for (**a**), but focusing only on: proportional growth (Prop), our measure (CTV) and log size difference (Log diff). **c** We do the same exercise as for (**b**) but considering an initial number of employees equal to 100 instead of 10. Notice that we proxy firm size (used when computing any of the growth measures) by the number of employees plus one

rates, and the number of employees plus one as a proxy for firm size (to avoid the existence of infinite negative growth rates), then the distribution of growth, conditional on initial firm size, has a left boundary that depends on the initial size itself: the support of the growth rate distribution, and in particular the minimum growth rate, is sensitive to the firms' initial size. Having such a distortion in the growth rate distribution can potentially bias a study on industrial dynamics and innovation, especially when extreme growth events (i.e. the tails of the growth distribution) deserve particular attention. A left truncation of the distribution characterizes all the measures of growth rate, but it has a particular disturbing impact in the case of the log difference proxy, because only in this case the left truncation is dependent on the size of the firms in the sample.

In order to clarify this, the heterogeneity across growth rate measures can be made explicit with a small experiment (see Fig. 5). To do so, we consider the 1-year growth rate for different initial firm sizes, comparing three growth indicators: proportional growth (Prop), log size difference (Log diff) and our measure (CTV), cf. Fig. 5 (top). As expected, the Birch index largely overemphasizes large positive events, but also associates larger negative values to decreases in size as compared with the proportional growth, CTV and log difference measures. Differences between the latter measures are better visualized in, cf. Fig. 5 (middle), where we do the same exercise as for the fist figure, but focusing only on: proportional growth (Prop), our measure (CTV) and log size difference (Log diff). In Fig. 5 (bottom), we do the same exercise as for Fig. 5 (middle) but considering an initial number of employees equal to 100. We can observe the sensitivity of the log difference measure to initial size: the higher the initial size, the lower the minimum log size difference; the log size difference is -2.4 (i.e. the opposite of the natural logarithm of 11, since we proxy firm size by number of employees plus one) for a firm exiting in t with size 10 employees in $t-1$, and -4.6 for a firm with initial size 100 employees. Instead, the minimum growth rate is always close to -1 in terms of proportional growth and close to 0 in terms of our own growth measure (CTV).

Data information

See Tables 7 and 8.

Table 7 Data cleaning and sample creation

	No. of observations	
Original data	62,705	
Drop if missing R&D		−31,650
Drop if R&D share >1		−344
Drop if $g^1_{i,t} > 2$		−81
Drop if $g^2_{i,t} > 2$		−49
Drop if $g^3_{i,t} > 2$		−14
Drop if $g^4_{i,t} > 2$		−15
Drop if missing $\overline{\mathrm{RD}}$		−9,782
Original data after cleaning	20,770	
Drop duplicates		−7,534
Without double counting	13,236	

Table 8 Structure of the panel before and after removing duplicates

	Wave 1 (1996)	Wave 2 (1998)	Wave 3 (2000)	Wave 4 (2002)	Wave 5 (2004)	Wave 6 (2006)	Total no. obs.	Total no. firms
Original data	8,554	12,524	10,623	10,525	10,667	9,812	62,705	36,542
Original data after cleaning	3,621	5,489	3,438	2,713	2,903	2,606	20,770	13,236
Without double counting (sample used: keep last)	1,428	3,457	1,981	1,657	2,107	2,606	13,236	13,236
Without double counting (alternative: keep first)	3,621	3,784	1,959	1,141	1,459	1,272	13,236	13,236

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